The State of Data Curation at NeurIPS: An Assessment of Dataset Development Practices in the Datasets and Benchmarks Track

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Abstract

Data curation is a field with origins in librarianship and archives, whose scholarship and thinking on data issues go back centuries, if not millennia. The field of machine learning is increasingly observing the importance of data curation to the advancement of both applications and fundamental understanding of machine learning models – evidenced not least by the creation of the Datasets and Benchmarks track itself. This work provides an analysis of recent dataset development practices at NeurIPS through the lens of data curation. We present an evaluation framework for dataset documentation, consisting of a rubric and toolkit developed through a thorough literature review of data curation principles. We use the framework to systematically assess the strengths and weaknesses in current dataset development practices of 60 datasets published in the NeurIPS Datasets and Benchmarks track from 2021-2023. We summarize key findings and trends. Results indicate greater need for documentation about environmental footprint, ethical considerations, and data management. We suggest targeted strategies and resources to improve documentation in these areas and provide recommendations for the NeurIPS peer-review process that prioritize rigorous data curation in ML. We also provide guidelines for dataset developers on the use of our rubric as a standalone tool. Finally, we provide results in the format of a dataset that showcases aspects of recommended data curation practices. Our rubric and results are of interest for improving data curation practices broadly in the field of ML as well as to data curation and science and technology studies scholars studying practices in ML. Our aim is to support continued improvement in interdisciplinary research on dataset practices, ultimately improving the reusability and reproducibility of new datasets and benchmarks, enabling standardized and informed human oversight, and strengthening the foundation of rigorous and responsible ML research.

1 Introduction

The NeurIPS Datasets and Benchmarks (D&B) track was created in 2021 to enhance the development of datasets in line with the exponential growth of applications of machine learning (ML). A key challenge this track aimed to address is that of datasets being used outside their original scope as benchmarks [43, 81, 87, 102] – among other potential issues, this creates the possibility of field-level overfitting, as well as unanticipated ethical and privacy problems. NeurIPS sought to address this by encouraging the development of new datasets for ML, improving the quality of datasets being produced, and emphasizing the importance of the role of data within ML. The introduction of new, tailored peer-review guidelines also enabled and incentivized publication of datasets and benchmarks. The D&B track is thus uniquely positioned to influence and guide the quality and ethicality of datasets being released and bolster responsible dataset development practices.

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Recent research in fairness, accountability, and transparency has proposed to reduce bias in models, via datasets, through the improvement of dataset documentation [29, 50, 52, 56, 61, 64, 86, 90]. Particularly, recent research on ethical data curation for ML datasets [47] emphasizes the adoption of concepts and processes from library and archival studies and digital curation in order to improve the documentation of dataset contents and data design decisions [47, 19, 39, 97]. **Data curation**, a subset of digital curation and information science, is "...the activity of managing data throughout its life cycle; appropriately maintaining its integrity and authenticity; ensuring that it is properly appraised, selected, securely stored, and made accessible; and supporting its usability in subsequent technology environments." [75, p. 203]. We recently translated data curation concepts for the ML dataset development context [11]. The results enable us to apply data curation to the field of ML so that dataset development practices can be evaluated and improved.

Contributions: Our goal is to document and improve the standard of dataset development in NeurIPS so that future benchmarks and datasets can be effectively found, easily accessed, ethically used, consistently evaluated, and appropriately reused. To these ends, we present a systematic dataset documentation evaluation framework to organize the assessment of curation practices for ML dataset development. The framework is composed of a rubric and toolkit developed through an iterative multi-stage process to arrive at the rubric elements relevant for evaluation and corresponding criteria for their assessment, as well as supplementary material packaged as a toolkit to aid in the application of the rubric. Here, we establish the feasibility of this framework as an auditing tool for dataset documentation by performing a systematic evaluation of a sample set of 60 datasets published in the NeurIPS D&B track between 2021-2023. We analyze the assessments to evaluate how data curation is currently performed in ML and show how it can be improved. Our results demonstrate that documentation quality varies widely across datasets and reveal a lack of documentation and reflexivity on environmental footprint, the situatedness and non-neutral nature of data, ethical considerations, and data management. We recommend how to improve this in Section 5 and make a proposal for NeurIPS peer-review changes.

2 Background

2.1 The Importance of Data in Machine Learning

Increasingly, machine learning research has turned towards the improvement of data to improve model results and fundamental understanding. Research areas include the role of data (distribution) in learning theory and generalization [6, 27, 26, 38, 101, 51], explicitly data-centric machine learning [25], the construction of datasets [3, 30, 46, 82, 85, 93], addressing a greater number of areas and problem domains [5, 23, 44, 48, 98, 103], the development of ethical models/frameworks around AI and data [2] within sound and music computing, computer vision, natural language interfaces, and more [7, 17, 24, 58, 92].

NeurIPS has responded to the rising urgency and recognized impact of data through the introduction of the Datasets and Benchmarks (D&B) track [102]. Submissions to the NeurIPS D&B track highlight aspects of data work critical to the development of machine learning datasets. Specifically, [84] looks at impacts of unmanaged citations of dataset derivatives, continued usage of datasets after their retraction, ambiguous dataset documentation, non-restrictive and ineffective licensing, and lack of long-term data stewardship. A data quality framework developed for datathons [62], is also applicable for the examination of data quality of ML datasets as it covers 5 broad quality dimensions. A checklist for ethical data collection of human-centric computer vision datasets highlights that further emphasis should be placed on moving away from general-purpose datasets to clearly-defined dataset collection, providing recommendations for obtaining consent and maintaining privacy, and proposing how to examine, acknowledge, and enhance dataset diversity [4].

In 2023 NeurIPS released a Code of Ethics [65] to supplement the NeurIPS Code of Conduct [74]. The code of ethics includes information on how to report and prevent harms from research that involves human participants, data concerns including privacy, consent, etc., and societal harms such as concerns of safety, security, discrimination, harassment, environment, human rights, and bias. Alongside this, there were ethics guidelines released for reviewers [71] which point reviewers to checklists and a framework for evaluating general ethical conduct, as well specifications for human-related data, data concerns around compliance, consent, and regulations, and negative societal impacts. Guides and further information about how to report on these areas have been released by NeurIPS

and others [13, 68]. Since 2021, the D&B track has seen immense growth and success, from 174 of 484 submitted papers accepted in 2021 to 322 of 987 submitted papers accepted in 2023 [67, 73].

As the landscape of data-focussed ML research continues to evolve, there remain open challenges for the field to tackle. For example, a review of AI impact statements in NeurIPS papers from 2021 [53] finds that 'agency' and 'responsibility' are two key themes in the statements whereby dataset creators feel they are not in control of the negative impacts of their work if it was to be misused by malicious users. Authors typically reassign the responsibility to identify and safeguard against potential negative impacts to other practitioners, or state that the potential negative impacts of their work are the same as those that exist for that domain, i.e., further work is needed to recognize contributions as non-neutral and take accountability of how design decisions impact outcomes [53].

2.2 Data Curation

Data curation's influences as a field include information sciences, digital libraries, and archival sciences [78, 88, 1, 49, 16, 39]. It thus has deep-rooted and established methods and discourse on how to maintain large amounts of data and manage ethical concerns. Data curation as a component of digital curation takes a **lifecycle approach** to the management of digital data [75]. Lifecycle approaches divide the digital curation practice into stages, which differ in their details but have in common a broad view including the pre-use, use, and post-use of a dataset. For example, the Digital Curation Center's model specifies 'conceptualize', 'create or receive', 'appraise and select', 'ingest', 'preservation action', 'store', 'access, use, and reuse', and 'transform' [34]. Each stage of curation consists of activities, designated roles and responsibilities, specified technical, legal, ethical, and operational considerations as well as policies that institutionalize the discussed activities and responsible parties [34].

ML studies on data practices ("...what and how data are collected, managed, used, interpreted, reused, deposited, curated, and so on..." [12, p. 55]) also called dataset development and data work most closely resemble examinations of the processes of data curation (despite often using the term to connote data collection, e.g., [56, 50, 35]). Other works in this space discuss the importance of documentation and propose new frameworks for it [8, 18, 29], review intrinsic and extrinsic biases in the dataset development process [64, 79, 63], and highlight the power dynamics involved in data quality, data work, and documentation [60].

In recent work [11], we performed a thorough literature review of data curation practices, translated them to be applied in a machine learning setting, and presented a preliminary analysis of a few NeurIPS D&B track datasets, focussed on the interdisciplinary process of adopting data curation for ML. Particularly, we highlighted the need for tools to translate the standards for transparency and accountability. In contrast to previously mentioned studies, our framework enables the application of *data curation* principles and concepts in practice.

Other authors also point to the need for dataset creators to *actively* document and steward their datasets [84], in contrast to much of the static documentation which is common in ML. These recommendations can be translated into practice-based processes: by seeing dataset development in ML as data curation and adopting its norms and practices, the NeurIPS community and ML research practices broadly can gain an elevated standard of documentation and resulting benefits to model performance, responsibility, and fundamental understanding.

3 Methods

Research Questions. What are the strengths and weaknesses of NeurIPS dataset documentation practices considered through a data curation lens? In other words, how well curated are NeurIPS datasets and benchmarks? To study this, we examine (1) What constitutes a well curated dataset? (2) How feasible is the adoption of data curation principles to assess ML datasets? and (3) What is the state of data curation at NeurIPS and how can it be further advanced?

Approach. We developed an evaluation framework to assess data documentation practices, i.e., curation processes, and applied it to recently published ML datasets in the NeurIPS datasets and benchmarks track. This track was precisely chosen because of its relevance in publishing such contributions but also in influencing the quality of datasets that are accepted. The evaluation framework consists of a rubric used to evaluate dataset documentation and design decisions and a

toolkit which supplements the rubric by providing additional information on how to apply the rubric effectively. This framework was applied to manually assess 60 ML datasets in three steps.

1. We established the **initial construction and design** of our evaluation framework consisting of the rubric and toolkit and reviewed the **preliminary feasibility** of the framework by applying it to 25 datasets across 4 rounds [11]. In these rounds, we continued to develop the framework iteratively based on the evaluation results [11]. We reflected and reported on the initial process of designing the framework such as the benefits resulting from the diverse perspectives of an interdisciplinary team, the lessons learned while applying the framework, and how we used the data from the initial application of the rubric to iteratively refine it and yield more consistent evaluations [11].
2. We **examined the consistency in application** by measuring inter-rater reliability (IRR). To claim that our framework is consistent, reliable, and accordingly feasible, we conducted another round of evaluations consisting of 5 datasets (round 4 and disagreement review) with the framework fully developed. We therefore address RQ 1 with our most updated version of the framework and RQ 2 with the final fourth round of evaluations that firmly establishes the framework's reliability through iteratively improving IRR results.
3. We applied this framework to assess 30 additional datasets to **evaluate current practices** of data curation in ML dataset development and areas where improvement was needed (RQ 3).

Evaluation Framework: We grounded our framework in data curation principles, emphasizing documentation, transparency, and ethical considerations. We started with key aspects of data curation relevant to ML and followed with iterative refinement through internal reviews and adjustments to evaluation criteria, guided by digital curation lifecycle models, FAIR data principles, and environmental sustainability and justice considerations. The rubric, provided in the Appendix, consists of 18 elements across five categories. In [11], we presented results from a training round and rounds 1-3. After round 3, we updated and refined the criteria for 13 elements and added additional guidance in the toolkit for interpreting authenticity, reliability, and representativeness. We present the up-to-date version of the framework along with the changes made between versions and their rationale in the Appendix.

The **scope** category has 2 elements, 'context, purpose, motivation' and 'requirements', which emphasize the requirement for a dataset creation plan and addressing intrinsic biases. The **ethicality and reflexivity** category has 4 elements, 'ethicality', 'domain knowledge and data practices', 'context awareness', and 'environmental footprint', covering a range of documentation requirements to increase reflection and accountability in the dataset creation process. The **data pipeline** category includes 'data collection', 'data processing', and 'data annotation', prompting reflection on how and why choices were made and their implications. The **data quality** category contains 'suitability', 'representativeness', 'authenticity', 'reliability', and 'structured documentation', to ensure the consideration of a broad set of qualities that impact how well a dataset can be appropriately and responsibly reused. The **data management** category covers FAIR principles [99] - findability, accessibility, interoperability, and reusability - included to evaluate the transparency of data management considerations. Each rubric element is assessed on minimum standard criteria (with a score of 'pass' or 'fail') that detail the expected level of documentation. Elements that pass the minimum standard are also assessed on a standard of excellence (with a score of 'full', 'partial', or 'none'). Therefore, the conceptualization of the rubric defines what a well-curated dataset must document. The **toolkit** is a supplementary resource that introduces concepts from data curation and serves as a manual to the rubric. It contains instructions and guidance on how to evaluate datasets, how to interpret specific elements, guiding principles, recommendations, FAQ, sample evaluations, a glossary, and further readings. The toolkit is provided in the Appendix.

Iterations. In order for data curation to provide robust norms for ML dataset development, our framework has to *enable consistent use*. To evaluate consistency, we measured inter-rater reliability (IRR) as we iteratively refined the rubric over multiple rounds of evaluation. The preliminary stage of refining the rubric occurred across the first 4 rounds of evaluations (namely training, round 1, round 2, round 3) [11]. Each round involved improvements based on feedback and observations, ensuring the rubric and toolkit were effectively refined and validated. This was structured around several key activities. We began with a training round to help reviewers become acquainted with the rubric and foundational data curation concepts, significantly reducing initial discrepancies and increasing IRR in the upcoming rounds. Following each evaluation round, we gathered feedback from reviewers and

identified specific areas of the rubric that needed adjustments to better convey the expectations and reduce ambiguity. We refined definitions, provided clearer examples, and better aligned the rubric elements with practical evaluation scenarios. This established preliminary feasibility.

Consistency. To establish the framework's feasibility and consistency, we performed additional rounds of evaluations. Across training to round 4, three reviewers assessed each of the 30 datasets in a fully crossed design [57] thus we calculated IRR using a two-way mixed, consistent, average-measures intra-class coefficient (ICC) to assess the consistency of the raters' evaluations of rubric elements measured on an ordinal scale across subjects [31]. In rounds 3 and 4, we additionally performed a "disagreement review". Once reviewers had completed their evaluations, they reviewed other evaluations and engaged in a brief discussion period in which they could debate, review, and update their scores and comments. Given the interpretative nature of the framework, this collaborative disagreement review enabled improved understanding of the rubric concepts and mitigated potential errors such as overlooking provided documentation. It also led to greater consistency while simultaneously leveraging the diverse perspectives of reviewers to enhance the richness and accuracy of the dataset evaluations. With the framework's feasibility established, we evaluated additional datasets.

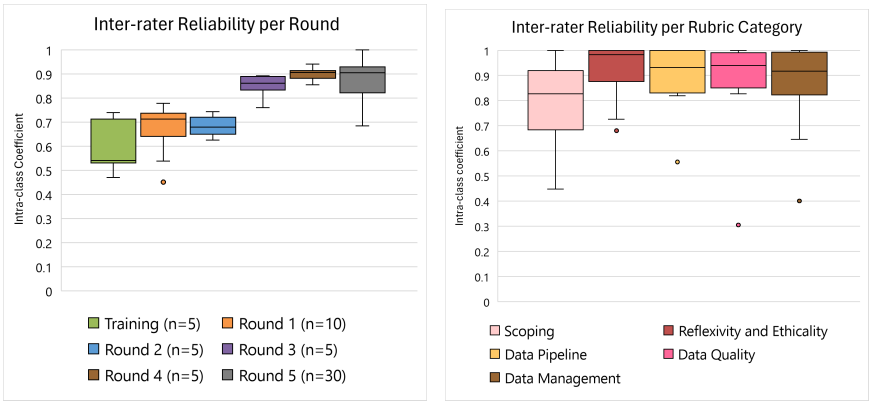
Application. To understand precisely how data curation can contribute to the advancement of ML dataset documentation practices, we performed a final round of evaluations (round 5). In this round, we evaluated 30 datasets published in the NeurIPS D&B track from 2021-2023. A full list of evaluated datasets from all rounds can be found in the Appendix. The datasets were randomly selected after filtering all published papers at the NeurIPS D&B track for dataset contributions. The filtering process is described in the Appendix. In the final round, four reviewers performed double coding for 30 datasets, each reviewing on average 15 datasets, including a disagreement review. Accordingly, we measured IRR with a one-way mixed, consistent, average-measures intra-class coefficient (ICC). After the disagreement review, additional corrections were made for consistency, see Appendix. All 60 dataset evaluations and analysis files can be found hosted on Zenodo [10].

Analysis. We analyze to what extent criteria were fulfilled for 1) each dataset and 2) each rubric element. This enables a review of whether data curation can provide guidance for documentation for NeurIPS datasets and precisely in what capacity that guidance is needed.

4 Results

R1. Inter-rater reliability suggests the evaluations are consistent and reliable. We observed a quantifiable improvement in IRR per dataset across successive evaluation rounds. The ICC values progressively increased moving from "fair" to "excellent" agreement among raters. In the final round, the median ICC value for the 30 datasets evaluated was 0.90 (Figure 1a). Despite the high level of qualitative human interpretation present when evaluating IRR across elements as compared to datasets, the final round had very high agreement, with ICC values with medians ranging from 0.83-0.98 across rubric categories (Figure 1b). The improvements in IRR confirm the effectiveness of our iterative refinement approach. By continuously enhancing the rubric and its guidelines, we achieved a high level of consistency in evaluations, demonstrating the rubric's potential as a reliable tool for assessing dataset documentation in machine learning. This high level of agreement underscores the clarity and effectiveness of the rubric's criteria in guiding evaluators to consistent outcomes. These findings are critical as they establish the rubric's credibility and pave the way for its broader application and acceptance within the ML community. Additionally, the findings demonstrate the utility and rigor of qualitative human evaluations. ICC values for each of 5 rounds is shown in Figure 1a and across rubric categories in Figure 1b. Additional results are provided in the Appendix.

R2. Documentation quality varies widely across datasets. To gauge the extent of documentation provided, we calculated for each dataset the percentage of rubric elements that received a 'pass' and 'fail' score for the minimum standard and a 'full', 'partial', and 'none' score for the standard of excellence. Since each dataset was evaluated by 2 reviewers and the rubric consisted of 18 elements, we averaged the score across both reviewers and divided by 18. The results are shown in Fig 2a and 2b. Across all datasets evaluated during the final round, one fulfilled 86% of the minimum standard criteria (highest pass rate), while another fulfilled only 39% (lowest pass rate), a 47% difference. The absolute difference between the best and worst performing papers at the standard of excellence criteria is similar, with the best-performing paper scoring 'full' on 50% of the standard of excellence and the two worst-performing receiving no 'full' scores. These results demonstrate that documentation varies



(a) IRR for evaluation rounds (b) IRR for rubric categories in round 5

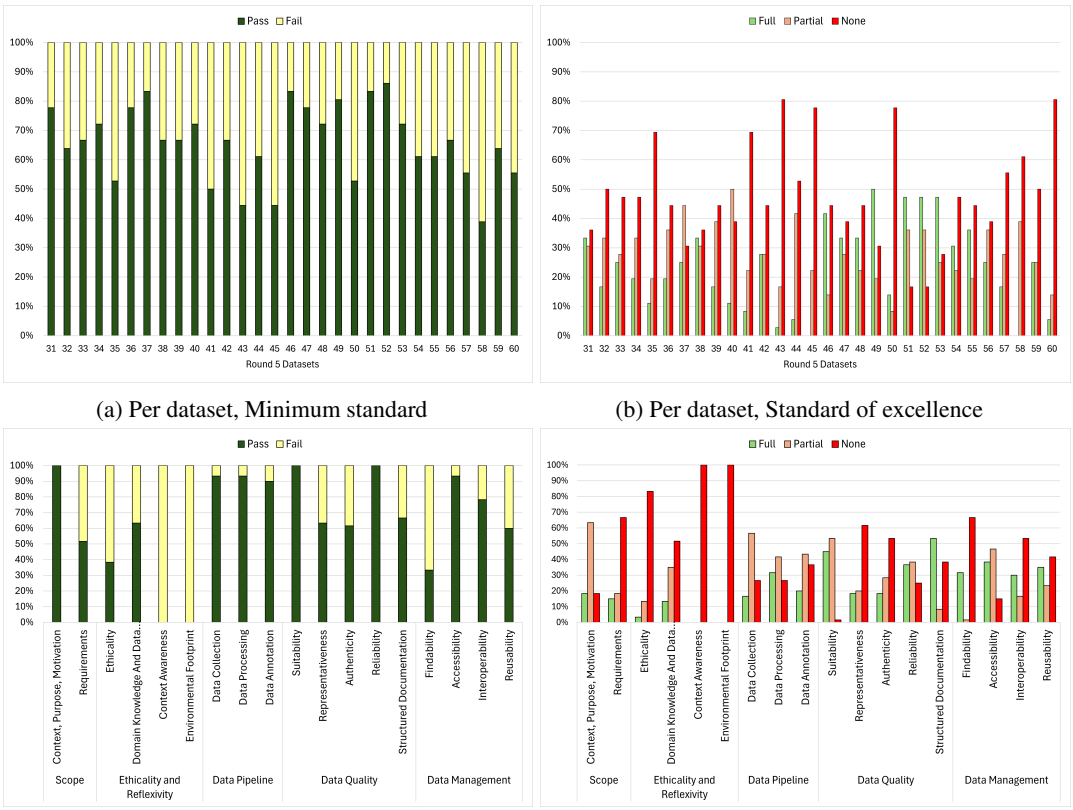
Figure 1: Inter-rater reliability (IRR) **(a)** Across evaluation rounds, and **(b)** Within round 5 across rubric categories. Improvement of IRR across rounds and ultimate high IRR across categories provides evidence that the multi-stage quality and consistency process described in Sec. 3 was successful. In addition to this quantitative measure, we conducted qualitative participatory evaluations with reviewers in each round; see **R1** and Appendix.

widely across datasets and there is great scope for improvement in documentation practices from a data curation lens, particularly to meet a standard of excellence.

R3. NeurIPS prioritizes model-work adjacent documentation. To analyze where data practices could be improved, we measured the completion of documentation for each rubric element and category by calculating the number of 'pass', 'fail' scores and 'full', 'partial', 'none' scores for all 60 evaluations (2 per each dataset in round 5) and divided the number by 60. Notably, NeurIPS papers tended to perform better at certain rubric elements than at others (see Figure 2c, 2d). Documentation for the minimum standard for 'context, purpose, motivation', 'suitability', and 'reliability' was 100% fulfilled. Additionally, all 3 elements in the data pipeline category were 93% fulfilled. This highlights the areas that are prioritized and considered primary for documentation by dataset creators. These are also areas that are standard to report for publication. NeurIPS has also been able to guide and encourage greater focus through the suggested submission requirements for 'structured documentation' (i.e., datasheets [29], data statements [8], etc.) and some aspects of the data management rubric elements. For example, documentation for a dataset clearly stated the problem domain of NLP and computer vision and the relevance of the new dataset being introduced in creating speech-based rather than text-based input for assistive devices ('context, purpose, motivation'), discussed the feasibility of their dataset ('suitability'), and provided a datasheet ('structured documentation').

R4. Documentation is rarely context-aware and typically does not quantify environmental footprint. The rubric elements with the worst performance across round 5 evaluations are 'context awareness' and 'environmental footprint', both with 0% pass rates of the minimum standard (and subsequently of the standard of excellence). Papers fail the 'context awareness' rubric criteria by not including a dedicated positionality statement (a statement of authors' institutional affiliations is not considered as a statement of or reflection on positionality). For the standard of excellence, less than 20% of papers receive a 'full' or 'partial' score for the 'ethicality' standard of excellence. That is: even those papers that make use of the proportionality principle and document informed consent tend to do so only as much as required by ethics checklists, with additional ethical discussion rarely included. The evaluated datasets also fail the 'environmental footprint' criteria because none of them quantitatively assess the environmental footprint associated with dataset creation.

R5. Documentation often remains incomplete. The results indicate that even for those datasets with well-documented elements for the minimum standard, rigorous documentation is ultimately lacking. For example, in the case of 'reliability', papers tend to pass the minimum standard by describing the phenomena represented by the data (e.g., describing the videos from which screen capture data were generated), but fail the standard of excellence by not providing a mechanism by which others could verify what was being represented (e.g., no way for anyone else to access the videos used to produce screen captures). As in the case of 'reliability', and as intended in the rubric's design, papers perform



(a) Per dataset, Minimum standard

(b) Per dataset, Standard of excellence

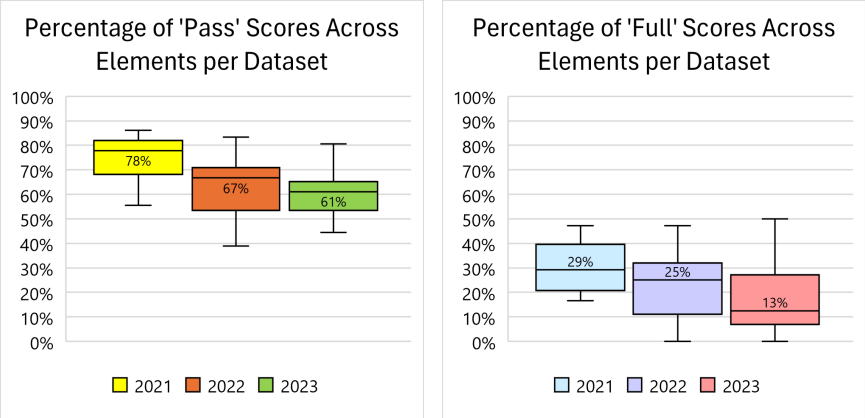
(c) Per element, minimum standard

(d) Per element, Standard of excellence

Figure 2: Percentage of completed documentation per dataset (a,b) and per element (c,d) in round 5 (i.e. after a multi-step iterative process to improve quality). In **(a)** we observe that the highest scoring dataset fulfilled 86% of criteria to meet the minimum standard of quality while the lowest fulfilled only 39%; in **(b)** for the standard of excellence we see similar spread (approximately 50% difference but lower attainment (highest fulfilled 50% of criteria, lowest two fulfill none of the criteria for excellence); see **R2**. In both **(c)** minimum standard and **(d)** excellence we observe that those elements more closely related to model-work (such as 'suitability' and 'reliability') are more consistently fulfilled; see **R3**.

better at the minimum standard than at the standard of excellence: 14 out of 18 rubric criteria have a minimum standard pass rate over 50%, compared to 1 of 18 with 'full' scores over 50% and 3 of 18 with 'partial' scores over 50% for the standard of excellence.

R6. Findings suggest no improvements occurred over time. We evaluated an even distribution of datasets published in 2021, 2022, and 2023 for round 5. Figure 3 shows the results of the percentage of 'pass' and 'full' scores across elements for each dataset summarized by year. Particularly, we can observe a slight downward trend in documentation scores across the years evaluated: from 2021 to 2023, the median percentage of 'pass' scores per dataset for the minimum standard goes from 78%, to 67%, to 61%, while the median percentage of 'full' scores per dataset for the standard of excellence goes from 29%, 25%, and 13%, respectively. In 2021, the call for papers for the D&B track required the submission of dataset documentation, URL for accessing the dataset, details about data licensing, hosting, and maintenance, and for authors to ensure easy reproducibility [66]. In the following years, additional requirements around datasets being in widely used formats, long-term preservation, inclusion of and access to metadata, and usage of persistent identifiers were added [69, 72]. Despite the increasing stringency of requirements, we could not find any evidence in this sample to suggest that the extent of provided documentation improved over time, pointing to the need for an encompassing structure and framework by which to assess documentation practices and pinpoint areas of improvement. Furthermore, the use of structured documentation also reduced over time, from 80% in 2021 to 50% in 2023.



(a) Minimum standard

(b) Standard of excellence

Figure 3: Temporal distribution across years 2021-2023, **(a)** 'pass scores' for the minimum standard of quality and **(b)** 'full scores' for the standard of excellence across elements. In both cases there is no change across time; see **R6**.

5 Discussion

5.1 How to Improve Data Curation at NeurIPS: Strategies and Resources

Our findings identify areas for which datasets have low or no documentation. To aid dataset creators in strengthening their curation processes, we recommend the adoption of the following methods and resources, particularly for the elements 'requirements', 'ethicality', 'context awareness', 'environmental footprint', 'findability', and 'reusability'.

First, to address **'requirements'** we echo recommendations regarding the creation of **purpose statements** [4]. Stating how dataset creators translated the "real-world" problem they are addressing into a "ML problem" for which the dataset is created [64, 79] promotes transparency. This process consists of numerous decisions, expertise, and assumptions that should be documented in order to understand the context in which the problem situation was framed. In cases of harmful ML models, it has been seen that this translation process can lead to the creation of bad proxy data that unfairly represents the real-world scenario [77]. Furthermore, sharing this process reveals the practicalities of performing data work which is often hidden and considered under-valued [33, 95]. Particularly, it is important for dataset creators to distinguish between the **initial formulation** of the problem **vs.** the **dataset creation scheme** detailing how the dataset development was actually executed. The latter is often documented after the development of the data and can be impaired by the "forgetting practice" of only recording conclusions [64]. As Muller et al. distinctly point out, "Measurement plans tend to record conclusions, not rationales… Other people then work with those conclusions, and have no way to access those unrecorded rationales." [64, p. 9].

We urge dataset creators to explicitly document how the benefits of developing their dataset outweigh the harms of creating it to improve reflection on **'ethicality'**. In other words, the **proportionality principle** must be considered. In ethics, it is understood that actions have positive and negative effects simultaneously. This is called the double effect. "Applications of double effect always presuppose that some kind of proportionality condition has been satisfied. Traditional formulations of the proportionality condition require that the value of promoting the good end outweigh the disvalue of the harmful side effect." [59]. The submission checklist for NeurIPS requires authors to document potential positive and negative societal impacts of their work; we support this and additionally recommend the checklist be amended to encourage comparison and reflection on these in proportion to each other, which very few datasets from our evaluations explicitly do.

'Context awareness' was not well demonstrated in any dataset we evaluated, correlated with the lack of positionality statements in the NeurIPS D&B track as a whole. Past research from the track has pointed to the importance of annotator **positionality**, as researchers' social identity and implicit biases impact data-related choices [4]; this recommendation is also made from a feminist

HCI (human-computer interaction) perspective with the goal to increase **reflexivity** in ML dataset development [91]. See Appendix for examples of positionality and reflection statements of this work.

Data curation in ML encompasses many phases, each responsible for significant emissions due to energy consumption [21, 36, 45, 55, 76, 80]. Several datasets in our sample ranged from over one million instances [37, 41, 89, 100] to several billion instances [22, 28, 32, 83]. Owing to their volume, these datasets are anticipated to have a significant environmental footprint, beyond the impacts associated with model training which have tended to be the focus in ML. There were no quantitative assessments of **'environmental footprint'** in the evaluated datasets. This quantification is crucial for several reasons: it allows for the assessment and comparison of carbon footprint across different projects, facilitating more informed decisions about resource allocation and model design [55, 94]. Understanding these impacts can also drive the development of more energy-efficient algorithms and hardware, contributing to broader efforts to mitigate climate change [40, 45, 96]. Moreover, as public awareness of environmental issues grows, the ML community faces increasing pressure to demonstrate accountability and progress toward sustainability [40, 80, 94]. Transparent reporting of carbon emissions can enhance the credibility of research institutions and companies in the field. By understanding where these emissions originate, researchers and engineers can better target interventions, such as optimizing algorithms for efficiency or sourcing providers with renewable energy for power-intensive tasks, to mitigate the ecological consequences of their work [40, 45, 96]. We provide a list of strategies in the Appendix on how to report environmental footprint for dataset development.

To improve '**findability**', we urge NeurIPS to require datasets to have **metadata** (not just data) assigned a persistent identifier and hosted in a searchable repository (such as Zenodo). While we recognize that having this requirement for all datasets may be infeasible due to volume, sensitivity, and other factors, having this information *for metadata* will help provide information about the dataset that will be available in the long-term, even if the data are gone. Although many datasets are provided on GitHub or platforms hosted by the dataset creators, these URLs suffer from a high likelihood of **link rot** (that the link will no longer be available over time) [42]. Lastly, to improve '**reusability**', we echo the inclusion of identifier information, dataset characteristics, and dataset provenance as outlined in The Data Provenance Initiative [54].

5.2 What Next: A Proposal for Peer-Review

Peer-review processes are constantly progressing with evolving needs, and they require multiple lenses [14, 15]. We propose that our evaluation framework can provide a structure that enhances the submission and peer-review process for the NeurIPS Datasets and Benchmarks track. Dataset creators, by applying the rubric and associated resources, would be more easily able to conduct their dataset development processes with data curation in mind. On the other side, dataset reviewers can use the rubric to evaluate dataset documentation, highlight targeted areas of improvement where data curation standards can be applied, and provide recommendations. The framework speaks directly to the evaluation of documentation required from peer-reviewers in the review form - "Documentation: For datasets, is there sufficient detail on data collection and organization, availability and maintenance, and ethical and responsible use? Note that dataset submissions should include documentation and intended uses; a URL for reviewer access to the dataset; and a hosting, licensing and maintenance plan." [70]. The presented framework allows for the systematic, precise, and encompassing evaluation of these details beyond the prompts present in the current review form, through the criteria presented for the elements in the data pipeline category (i.e., data collection and organization), the data management category based on the FAIR principles [99] (i.e., availability and maintenance), and the ethicality and reflexivity category (i.e., ethical and responsible use). The use of this framework would also enable reviewers to consistently determine whether an additional ethics review is needed. A past consistency experiment for peer-review at NeurIPS in 2014 showed that "if the conference reviewing had been run with a different committee, only half of the papers presented at the conference would have been the same" [20, p. 3]. The 2021 version of the experiment was "...consistent with the 2014 experiment when the conference was an order of magnitude smaller." [9]. Our framework can thus help provide a means of consistency in terms of dataset documentation. We suggest incorporating the framework by introducing a dedicated 'dataset documentation' reviewer role to the NeurIPS D&B track. This can initially be similar to the ethics reviewer, who performs reviews only for those papers that are flagged, but may later evolve to be a part of the core peer-review team. We recommend a dedicated reviewer because of the relatively intense process of evaluating each dataset and the specialized skillset that

it will require. Although we found that the time requirement to evaluate each dataset ranged from 35 minutes to 2 hours, the average time in later rounds was limited to 1 hour. Additionally, as with ethics reviews, the results from the dataset documentation review should advise the acceptance of the paper as poor documentation ultimately leads to poor reusability and reproducibility which would defeat the purpose of the D&B track.

5.3 Limitations

We identify five limitations of our work. **1.** The results we showcase are based on the sample set of datasets we evaluated. Although these datasets were randomly chosen and evenly distributed between 2021-2023, there is a chance for the selected datasets to be unrepresentative of the datasets and benchmarks published at the NeurIPS D&B track as a whole. **2.** Our analysis is based on descriptive and interpretative evaluations completed by a mix of reviewers. Although we took careful steps in our iterative process to clarify and normalize standards of interpretation, all results are contingent on the human processes of differing evaluation styles. As with all peer-review, the results are thus dependent on the reviewers. **3.** It is understood that a given reviewer would evaluate each element in the rubric similarly across all datasets. However, we also conducted a disagreement review. This means that a reviewer could change their perspective for a specific element based on the comments of another reviewer, if a disagreement was flagged. This does *not* mean that the reviewer would then update their scores and comments for that element for all *other* datasets they evaluated. Thus some inconsistencies in how the one element is evaluated across all the datasets might be introduced as the cost of improving within-dataset review quality. We believe the impact of this limitation is low, as our results showed minimal disagreement in the final round (see Figure 1a). **4.** Our rubric is designed to enable qualitative and holistic evaluation of each paper on a standardized basis. We believe strongly in the merits of this approach, however it does limit the amount of insight we can have about how properties of the dataset itself influence curation practices. An interesting complementary future approach to study this would be to code characteristics of datasets and see if the trends we identify vary when decomposed by these characteristics, i.e., whether there are specific documentation trends across types of ML datasets or metadata. **5.** Using documentation to understand the curation process is not a substitute for being directly involved in the process or communicating with the dataset creators. As such, it is possible and ultimately a limitation that the reality of data curation is more complex than what is covered in documentation or our framework. In such cases, things can become overly simplified in the documentation and auditing process, e.g., box ticking instead of genuine reflection and evaluation. An ethnographic study of data curation would yield different, additional, insights that we cannot provide. This is currently a limitation and opportunity for future work.

6 Conclusion

By giving datasets and benchmarks a dedicated venue, NeurIPS has sent a clear message that dataset quality is the foundation of continued progress in ML applications and fundamental understanding. There is no better database of knowledge than data curation to aid in this venture. Our evaluation framework adopts concepts from these fields for ML and provides a practical lens on how NeurIPS can spearhead the requirement for rigorous data curation in ML. The enhancements due to the framework are designed to improve the quality, ethicality, and human oversight of new datasets and benchmarks, fostering greater scientific integrity and advancement.

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